Recognising Movement and Gait by Masking Functions

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Abstract. We present a new area-based measure that can not only analyse motion (such as to highlight human movement) but also for biometric purposes to recognise people by the way they walk. The technique operates by measuring the rate of change of area in a way controlled by masking functions. We show how this approach can be used to determine human behaviour, as opposed to animal movement, and give illustrative results of its potential to recognise people by their gait.

Introduction

It would appear intuitive that human gait differs from animal gait. As yet, however, there have been no studies, by computer vision techniques, aimed to confirm this. The notion that human gait is a biometric has appeared recently and is aimed primarily to recognise a subject by the way they walk. Gait has several advantages over other biometrics. It is difficult to disguise (in fact, disguising ones gait only has the effect of making oneself look more suspicious!) and gait can be recognised from a large distance where other biometrics fail, and it is a non-invasive technique.

Medical studies [1,2] support the view that if all gait movements are considered then gait is unique. Psychological research from Johansson [3] shows that humans have a remarkable ability to recognise different types of motion. Johansson performed an experiment with moving light displays attached to body parts and showed that human observers can almost instantly recognise biological motion patterns, even when presented with only a few of these moving dots. A more recent study by Stevenage [4] again confirmed the possibility of recognising people by their gait, but now using video. The study confirmed that, even under adverse conditions, gait could still be perceived. Psychological and medical studies therefore clearly support the view that gaits can be used for recognition.

Approaches to gait recognition can be divided into two categories: model based and holistic. Both approaches analyse sequences of images of walking humans for recognition purposes. The holistic approach considers whole body movement Examples of this type of approach include Murase and Sakai [5], Huang [6] and Little and Boyd [7]. Model based approaches aim to explicitly model human motion and rely on human movement being tracked and a model being fitted to the image data. An example of this approach is by Cunado [8]. Performance of this technique was good with high recognition rates, however the computational costs of this approach are high. None of these approaches has explored the possibility of identifying humans by their gait, though this would not appear unfeasible. For this, the holistic approaches would require more sophisticated training and the model-based ones a new model. Our new approach relieves these difficulties, whilst accruing the benefits of both strategies.

We present a new area based metric for gathering statistical data intimately related to the nature of gait. The technique will be performed upon both human and animal silhouettes and differences between the two will be examined. **Fig. 1** shows an example of silhouette extraction from a human and animal gait sequence. In this report we assume that the subject is walking normal to the camera's plane of view.

Fig. 1. Images converted to a silhouette

Gait Masks using Human Silhouettes

Gait masks are a new approach to gait recognition aiming to combine some of the elements of both the holistic and model based approaches. The disadvantage of traditional holistic approaches is that they simply derive data that is different for each class. They have no "knowledge" of what each class represents; given pictures of an elephant rather than a human subject and a traditional holistic approach would try to classify the subject in the same way. In contrast, current model based approaches would be difficult to extend to non-human gait.

Gait masks aim to combine holistic and model-based approaches by using statistical data that is intimately related to the nature of gait by transforming human silhouettes. **Fig. 2** shows examples of some gait masks.

Fig. 2. Sample gait masks

Each gait mask aims to isolate a portion of the image and measure its change in area. The gait masks were chosen intuitively to represent the area of the image most likely to provide meaningful data about the gait of a subject. **Fig. 3** shows examples of the results from **Fig. 2** on human silhouettes.

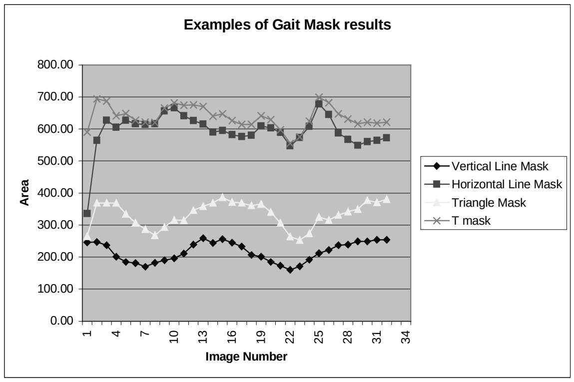

Fig. 3. Sample Gait Mask Results from one subject using 4 separate gait masks

The gait masks are combined with the silhouettes using the procedure detailed below. The set C_p labels each set of sequences of each individual person. Each item in the set ($\mathbf{S}_{P_j}$ **)** represents sequence *j* of person *p*.

$$C_p = \{\mathbf{S}_{p_j}\} \qquad \textbf{(1)}$$

The set T_{p_j} represents the individual images (silhouettes) in each sequence from each subject. Each member of the set $\mathbf{S}_{p_j}(t)$ represents a specific image (*t*) as a vector from person *p* sample *j*.

$$T_{p_j} = \{\mathbf{S}_{p_j}(t)\} \qquad \textbf{(2)}$$

The set *K* represents the set of gait masks, M_n, where each member represents each individual gait mask, each represented as a vector.

$$K = \{\mathbf{M}_n\} \qquad \textbf{(3)}$$

For each gait mask, *n*, and each person *p*, and each sample *j*, **R** is the projection of each sample into a new space using gait mask $\mathbf{M}_n$.

$$\mathbf{R}_{np_j}(t) = \mathbf{M}_n \cdot \mathbf{S}_{p_j}(t) \qquad \textbf{(4)}$$

The "vertical line mask" produces output that is sinusoidal in nature. The peaks in the graph represent when the legs are closest together and the dips represent where the legs are at furthest flexion. The gait masks therefore provide statistics that are intimately related to the mechanics of gait.

It is possible to use these graphs, produced using the gait masks, to provide recognition capabilities. By comparing the graphs using least squares and using a database of all samples and finding the closest match, recognition rates of over 80% are possible (dependent on the mask chosen). Since subjects start their walking cycle at different points, the graphs are compared at all possible shifts along the axis and the maximal correlation is taken. **Table 1** shows the recognition rates of various gait masks using this technique on a database of six human subjects with four samples each.

Table 1. Recognition results from various gait masks.

Gait Mask	Recognition Rate	Gait Mask	Recognition Rate
Horizontal Line Mask	71%	Bottom Right Mask	38%
Vertical Line Mask	83%	Triangle Mask	63%
Right Half Mask	42%	T Mask	71%
Left Half Mask	33%	Bottom Half Mask	54%
Bottom Left Mask	42%	Mid Triangle Mask	83%

The results from the vertical line mask (recognition rate 83%) were most encouraging as the output from this mask was directly related to the gait of the subject. However, once the input silhouettes were corrupted by even small amounts of noise the recognition rate dropped dramatically. Consequently, we decided to look at the results from this mask in greater detail.

To recognise a subject by their gait we are primarily concerned with the AC component of the data, that is the temporal component of the data. The DC component of the data represents static data about the subject; this could easily change due to the subject carrying something for example. The temporal nature of gait should be consistent amongst samples of the same person. To be sure that we were not discriminating between subjects based upon where in the gait cycle filming started, all data was aligned so that the walking cycle started at the same point. **Fig. 4** shows the sinusoidal patterns generated using the vertical line mask from 4 different people. Using the least square correlation technique, poor recognition rates were achieved. Using a more sophisticated technique, Canonical Analysis (CA), resulted in a dramatic performance increase.

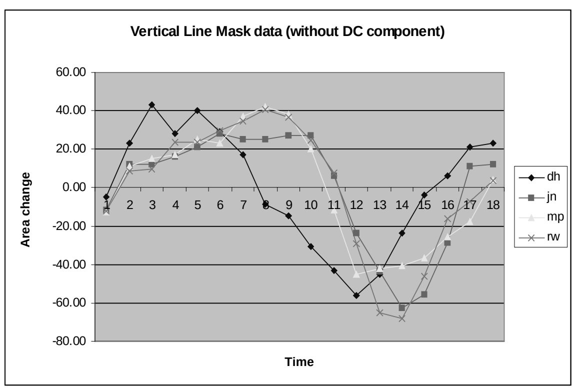

Fig. 4. Sinusoidal Patterns from 4 people using Vertical Line Mask

CA was used to produce a set of axes on which to project the data (the canonical axes). The data was divided into a set of training and test data. The training data consisted of three samples from each of the six subjects. The centroid of each subject in canonical space was recorded and the distance between this centroid and the test data was also noted. This was then used to calculate the recognition rate on the SOTON database. Initial results were promising with a recognition rate of over 80% and good class separability. To further evaluate the performance of the new technique the system was also tested on a larger database consisting of the SOTON database and each of the samples corrupted with various amounts of noise (1%, 2%, 4% and 8% noise). Performance remained high with a recognition rate of over 80% even in the presence of noise.

Gait masks using animal data

Discriminating between solid objects and articulated ones would appear much less demanding than the ability to discriminate between animal and human movement. This could be achieved by holistic approaches, with appropriate training. On the other hand, gait masks can be used to quickly distinguish between the motion of a biped (e.g. a human) and a quadruped. The single vertical line mask was used to provide data to discriminate between human subjects. Using this technique with animal data yields ineffectual results that provide no information about the gait of the subject. This is simply because the center of a quadruped provides very little temporal information, as illustrated in **Fig. 5**. By simply looking at the structure of the graphs it is clear that it is simple to distinguish between human and non-human gait.

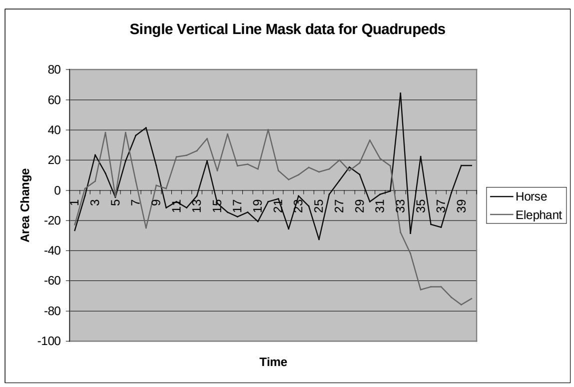

Fig. 5. Vertical Line Mask data using Animal Silhouettes

To provide information more relevant to the subject being analysed the gait masks were modified. Two vertical line masks were used, instead of the single vertical line mask used for human gait. By using these new gait masks it is possible to extract information relative to the subject being studied, as illustrated in **Fig. 6**.

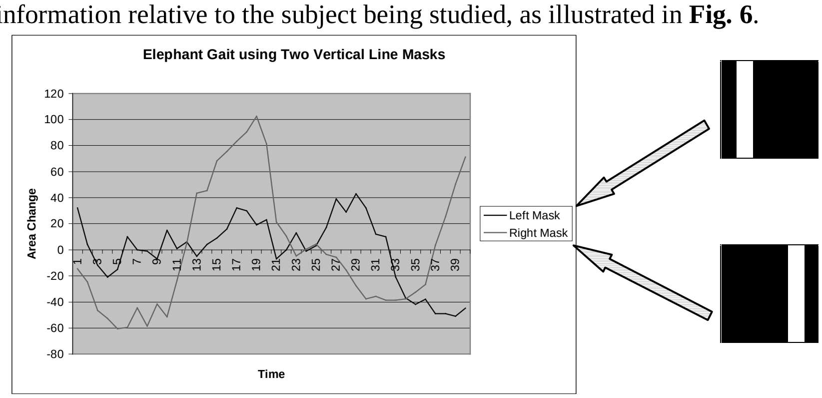

Fig. 6. Gait of an elephant described by Two Vertical Line Masks

By using the right mask the sinusoidal pattern of motion is clearly evident. The left mask data is not of a sinusoidal nature which is due to the trunk of the elephant swinging across the legs. This shows how the gait masks need to be adapted for each animal analysed. It also illustrates how gait masks can be used to provide information about gait for subjects other than humans.

In the future gait masks could be used for classification purposes. Given a database of various walking species, it should be possible to distinguish between species using gait masks. This would be of particular use for database browsing.

Conclusions

We have presented a new area based metric for gait recognition that produces good results on a small database. We have shown (by removing the DC component of the data) that recognition is possible by only using the temporal components of the silhouette sequence. The technique produces encouraging results on a database of human subjects with recognition rates of over 80% even in the presence of noise.

Additionally we have shown the basic premise of gait masks is applicable to areas other than using human gait as a metric. Gait masks can provide information about the walking cycle that could be used to provide information such as the cadence of the subject.

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